

University of Groningen

Alternative price indices for computers in the Netherlands using scanner data

Mulligen, Peter Hein van

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version

Publisher's PDF, also known as Version of record

Publication date:

2003

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

Mulligen, P. H. V. (2003). *Alternative price indices for computers in the Netherlands using scanner data*. s.n.

Copyright

Other than for strictly personal use, it is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license (like Creative Commons).

The publication may also be distributed here under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license. More information can be found on the University of Groningen website: <https://www.rug.nl/library/open-access/self-archiving-pure/taverne-amendment>.

Take-down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Downloaded from the University of Groningen/UMCG research database (Pure): <http://www.rug.nl/research/portal>. For technical reasons the number of authors shown on this cover page is limited to 10 maximum.

**Alternative Price Indices for Computers
in the Netherlands based on scanner data**

Research Memorandum GD-65

Peter Hein van Mulligen

**Alternative Price Indices for Computers
in the Netherlands using Scanner Data**

Research Memorandum GD-65

Peter Hein van Mulligen

Groningen Growth and Development Centre

July 2003

Alternative Price Indices for Computers in the Netherlands using Scanner Data

Peter Hein van Mulligen

Groningen Growth and Development Centre
University of Groningen

July 2003

Abstract¹: Using a scanner data set that covers nearly all computer sales in the Netherlands for a period of three years, this paper investigates whether there is a significant difference between a matched model index and a hedonic imputed index, which also takes non-matched observations into account. The result of this study was that this does not appear to be the case. The lack of significance of the difference can be attributed to two reasons: the high share in sales values of the matched items, and the mediocre fit of the hedonic model. Given the fact that an earlier study based on a different data set (Van Mulligen, 2002) also pointed out that the difference between a matched model index and a hedonic imputed index is small, we draw the conclusion that making explicit adjustments for non-matched items is not necessary.

Although the official CPI for computers also uses the matched model methodology, it appears to introduce a substantial downward bias in the actual quality adjusted price index, due to biased sampling and the lack of representative weighting of individual items. The main area for improvement of the CPI for computers (and possibly other durables as well) lies therefore in more frequent sampling, weighting and chaining of the indices rather than making explicit quality adjustments.

Keywords: Hedonic prices, CPI, computers, scanner data

¹ This paper is a rewritten version of a chapter in van Mulligen (2003) and is also published as working paper by Statistics Netherlands.

1. Introduction

Since their introduction in the early 1980s, personal computers (PCs) have become ever faster and more powerful. This is probably best summarised in what is now known as ‘Moore’s Law’, which states that the computing power of computers doubles every eighteen months.

Traditionally, the introduction of new goods and rapidly increasing quality of products² poses difficulties for the construction of price indices, which do not always take these phenomena into account. This fact is well illustrated in, for example, Boskin *et al.* (1996) and Wyckoff (1995).

There are two reasons why statistical offices, who are the main producers of price index numbers, face these difficulties. First, they lack adequate tools to deal explicitly with new goods and changing quality. Triplett (forthcoming) describes the methods used by statistical agencies to deal with these problems. All these methods make implicit assumptions about the degree of quality change, some of them using subjective assessments.

Second, they usually relate prices of products to their prices in some reference period. In the case of new goods or changing quality, this reference period is usually too far off in the past. This results in a rapidly decreasing number of items of which prices can be matched, sometimes called ‘sample degradation’ (Silver and Heravi, 2002b).

Although these two causes are related, they are in effect separate problems. Most criticism directed at the ‘biased’ official price indices is aimed at the first problem, whereas it is equally likely that the second problem, the use of a fixed reference period which is revised only after several years, causes much damage. Making chained price indices would probably mitigate the effect of new and better goods, especially if the chaining is done very frequently.

The procedure of chaining indices between relative short periods is adopted by Aizcorbe *et al.* (2000), which they dub ‘high frequency matched models’ (HFMM). They argue that if the periods of observation are close enough, the traditional matched model method provides enough matches as a share of the total value of sales. In this case, explicitly adjusting for quality differences and new products is not deemed necessary. Actually, using a regression based method they find price indices which are nearly identical to the HFMM ones.

This reasoning has provoked an argument between on the one side the defenders of the matched model method, and on the other those who think that explicit quality adjustments are still necessary, preferably in the form of the hedonic method. The latter side usually attacks the use of fixed reference periods by statistical agencies, which leads to ‘sample depletion’ (Silver and Heravi, 2001). On the other hand, the defenders of the matched model method aim their criticism mainly at the dummy method variant of the hedonic method, a variant which is usually not proposed by defenders of the hedonic method.

The correct measurements of price indices for computers is important for several reasons. One of these is the use of price indices as deflators of nominal output. Different countries use different methods to deflate the output of their information and communication technology (ICT) producing sector, which

² Strictly speaking, a good with a different quality would count as a new good. Here, a ‘new good’ is defined as a completely new product, like the first VCR or cellular phone. Goods with different quality are other (usually better) variations of an existing good, like a PC with a 1500 MHz processor vs. a PC with a 1200 MHz processor. These can be considered as new models rather than new goods.

leads to incomparable figures for the real growth in output and productivity in the ICT sector; this was well illustrated by Wyckoff (1995), and still causes some controversy (Deutsche Bundesbank (2000), Schreyer (2002)).

From an expenditure point of view, price indices serve a similar purpose as measurements of the cost of living. Scholars who are interested in relative levels and growth rates of purchasing power need accurate and comparable measures of the change in cost of living. Like output deflators, consumer price indices (CPIs) also suffer from a lack of international comparability. Although it is only implemented in official price statistics of few countries, the hedonic method seems an appropriate way to adjust for the rapid rate of quality changes in computing equipment.

The present paper tries to address these points for computers in the Netherlands. Alternative computer price indices are calculated using a scanner data set which was kindly provided by GfK Netherlands, a marketing agency. With this data set, several matched model indices are confronted with hedonic indices and the official Dutch CPI for computers.

This data set contains the near ‘universe’ of all computer sales in the Netherlands from January 1999 to January 2002. Detailed information on prices, specifications and quantities sold in nine different outlet types is given for three types of computer equipment: personal computers, notebooks and servers. The main purpose of this paper in general is to find out whether the hedonic method is really the preferred method for calculating accurate price indices for computers.

2. The current practice at Statistics Netherlands

For the construction of the price index for computers, Statistics Netherlands collects data from websites of several computer retailers. This method of data gathering replaced the former method in February 2001. Prior to this, data were collected from advertisements in computer magazines. Mostly the same retailers were followed before and after February 2001.

The computer price index consists of two parts: systems and components. A system is a ‘complete’ set, consisting of a computer box, keyboard, mouse, and in most cases a monitor. For the CPI, two kinds of components are used: printers and monitors. In this study, only systems will be the topic of interest.

Essentially, the Statistics Netherlands price index for computers is a matched model chain index (Elfering, 2001). Since computers increase in quality very rapidly, each computer system is sold for only a few months. For each retailer in the database, Statistics Netherlands tracks all computer systems in the data set during the period in which they are sold. Within this period, the computer system usually changes only little, so that it’s possible to construct a matched model index for this system for this particular retailer. In the period of its appearance, this index is chained to the price index for all systems. For example, the price index for all systems in January 2000 was 14.67 (with September 1997 = 100). A system that was introduced in this month will therefore have a price index of 14.67. When its price has decreased with 10% one month later, its index for February is therefore $0.90 \times 14.67 = 13.2$. This is what Triplett (forthcoming) calls the ‘imputed price - implicit quality adjustment’ (IP-IQ) method.

This method is applied for all systems for all retailers in the data set. When a system witnesses a change in, for example, its hard disk, working memory, or monitor, an option pricing

method is used to discount for this change, if possible. For example, if a system comes with a 17" monitor in one month, but a 15" monitor was included in the previous month, the prices of 17" and 15" monitors sold separately are compared. This price differential is considered as a quality change, and subtracted from the new price. When a system comes with a new processor, however, it is considered as an entirely new system, and no quality adjustment will be carried out. It enters the index as a 'new item'. Most quality changes are brought about by a different processor, so the option pricing method is only occasionally used.

For the sake of reliability and representativeness, a system will only be part of the final index if at least three retailers sold it in that month. For this purpose, the processor is the only criterion. So, if at least three retailers sell a system with a 900 MHz processor of a certain type, the indices of all these systems will be included in the final index. These systems can witness differences in other characteristics between the retailers. This data trimming makes sure that only 'mature' systems enter the index. Systems that are only sold by a few retailers are mostly very new or nearly obsolete, and such systems usually witness different price behaviour than other systems. The composite price index is an unweighted arithmetic average of the price indices across all systems and retailers.

Furthermore, only computer systems with particular processor types are used. The database containing all advertisements includes information on a lot of computers with other types of processors, but they are excluded from the CPI. Additionally, not all systems in the CPI could be singled out in the database. Table 1 shows the number of observations by month for the entire database, the number of observations from the dataset that are used for the CPI, and the total number of observations in the CPI. Although the total number of observations remains fairly constant in this period, the number that is used for the CPI declines steadily. It seems likely that this will increase the 'outside the sample' bias, caused by the fact that actual items are left out of the index because they cannot be matched.

Table 1

Number of observations in the total data set and the CPI

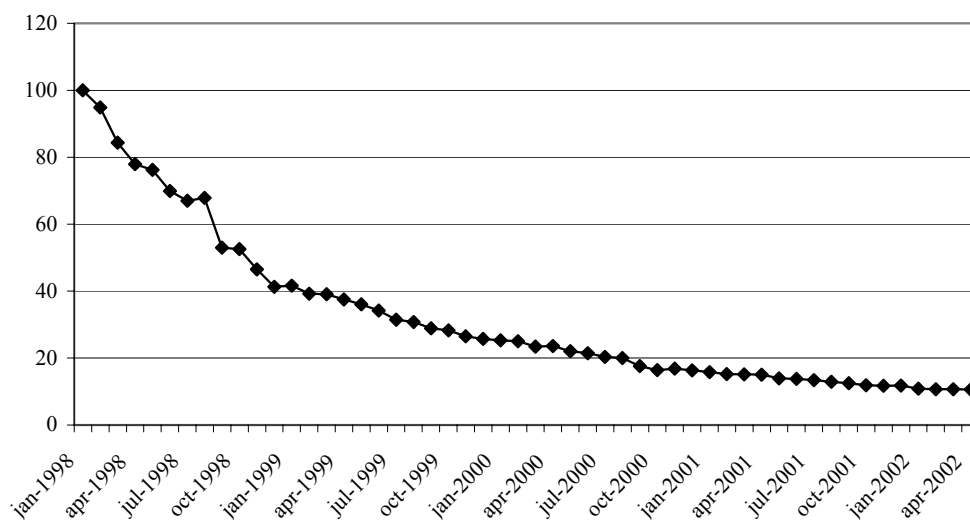
	Total data set	CPI
September 1999	136	43
October 1999	119	35
November 1999	105	39
December 1999	133	31
January 2000	113	31
February 2000	123	27
March 2000	122	17
April 2000	107	25
May 2000	113	13
June 2000	127	14

Source: CBS

Summing up, it is clear that in the price index for computer systems compiled by Statistics Netherlands, only 'like' is compared with 'like'. We can therefore expect a deceleration in the index, since all systems witness a price decline over their entire existence. As can be seen in figure 1, this indeed proves to be the case.

Figure 1.

Dutch CPI for computer systems, January 1998 - April 2002



Since only prices of identical computer systems are matched, there is no room for a quality bias caused by matching different products. Such a bias is also known as the ‘inside the sample’ problem (Triplett, forthcoming). There is no ‘sample degradation’ (Silver and Heravi, 2001) caused by keeping the reference period fixed. In addition, the ‘outside the sample’ bias is relevant to the extent that the data set used for the CPI is not representative for all computers sold in the Netherlands. Given the declining number of observations that are used for the CPI, this bias looks not unlikely.

3. Estimating hedonic indices using scanner data

With the increased use of bar code scanning at retail outlets, a wealth of data on retail transactions has come about. These data are called scanner data and are usually collected by marketing agencies like GfK, AC Nielsen, DataQuest and others to perform market research. They are also increasingly being used by economists.³ As scanner data contain information on prices, quantities sold and in many cases also on specifications, scanner data lend themselves very well for the construction of price index numbers and the application of hedonic regressions.

This section gives an account of research that was performed on a scanner data set on computer sales in the Netherlands. With these data matched model indices and hedonic prices indices are constructed.

Data

The data set provides monthly data on transaction prices, quantities sold and several characteristics of nearly all computers sold in the Netherlands from January 1999 to January 2002. GfK aggregates the data by outlet type, of which nine different types are distinguished: buying groups (BUYING), chain stores (CHAINS), computer stores (CS), department stores and mail order houses (DEPMOH), independent retailers (INDEP), office equipment retailers (OER), photo retailers (PRT), system and software houses (SH) and telecom specialists (TCS). According to the descriptions provided by GfK, two of these outlet types (OER and SH) mainly sell to businesses, whereas the rest supply the bulk of their sales to private consumers. All outlets with a substantial amount of computers sales are fully covered by GfK. In these cases GfK gets the sales data directly from the company’s headquarters. For small companies with a limited number of outlets and sales a sample outlet is taken. The total number of sales of this outlet is then multiplied by the number of outlets of the particular company to provide an estimate of its total sales. Since the largest part of computer sales takes place in the bigger stores, the share of these ‘extrapolated’ sales is fairly small. Therefore the GfK data set provides a near full coverage of the universe of computer sales in the Netherlands.

Individual computer models (hereafter called ‘items’) are given a unique product code based on the bar code. If bar codes correspond to unique computer configurations, we can be sure that a product match based on the product code is exact. For items with the same product code, the characteristics included the data base were indeed identical. However, the data set only contains a limited set of characteristics, so we can only assume that the other unobserved characteristics are

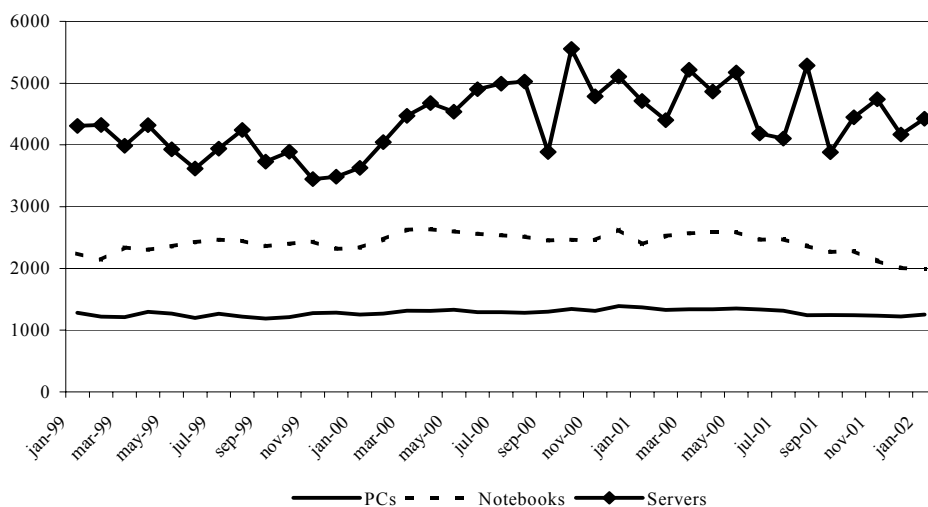
³Examples are Ioannidis and Silver (1999), Silver and Heravi (2001, 2002a, 2002b) and Heravi, Heston and Silver (2003).

identical as well, to be certain matching is exact. Although they could not provide additional information on unobserved features, GfK ensured that these were identical too. The quality of indices based on these scanner data therefore depends on the plausibility of this statement by GfK.

Computers can be sold at different outlet types. Within an outlet type the price of an item is the average transaction price across all outlets, weighted by quantities sold. The prices in the data set are therefore actually unit values. Since each item is unique, only prices are averaged. Characteristics are the same for each outlet within an outlet type, and the quantities sold can simply be added.

The data set consists of three different kinds of computer equipment: personal computers (towers and desktops), notebooks and servers. Since these are different products, separate hedonic functions and price indices will be estimated for each. The number of computer sales follows a cyclical pattern that is especially strong in the case of PCs. Computer sales (measured in physical units) peak every March and December (with a relative decline in January and February), whereas the trough is between May and August.

Figure 2
Unit values of PCs, notebooks and servers in euros,
The Netherlands, January 1999 – January 2002



Since the main focus of this paper is on the calculation of price indices, the average prices, or unit values, of computer equipment are shown here by way of comparison. A unit value for computers as presented here contains a strong inside the sample bias, because it explicitly matched computer prices regardless of changes in quality. Figure 2 tracks the unit values in euros of the three types of computer equipment. The unit values of notebooks and especially PCs remain fairly constant during the period under consideration, whereas the average price of servers shows a more erratic behaviour.

As pointed out above, the number of characteristics in the data set is limited. The main performance characteristics are processor speed in MHz (SPEED), storage capacity of the hard disk in MB (HDISK) and the memory capacity in MB (MEMORY). These are the only quantifiable, continuous variables which are given for each type of computer. For notebooks there is one additional

variable, namely the size of the screen in inches (SCRSIZE). The remainder of the characteristics is qualitative, and can be used in hedonic regressions only as dummy variables. These include the presence of a monitor (MONITOR) and USB port (USB), the screen type in the case of notebooks, the type of processor and the brand of the computer. If the item has no brand (which is the case, for example, when a consumer selects his own configuration), it is labelled as a clone.

The small number of physical characteristics is a disadvantage of the database. No information is available on graphical cards, sound cards, the type of computer, included operation system and application software, and so on. Therefore, we can expect that a relatively large part of the variation in prices cannot be explained by the variation in specifications listed above, unless there is a one-to-one relation between unobserved variables and observed ones, which is not likely. On the contrary, if unobserved variables are disproportionally correlated with included characteristics, then unobserved variables will bias the estimates of the coefficients of the hedonic regressions. This is true whether items with the same product code are exactly identical or not. If they are not, matched model indices will be biased, too. The latter is a potential drawback of the data base, as we have to trust the statement by GfK that matches are exact.

A strong point of the database is that it contains nearly all computer sales during this period, so we know that it is by definition a very good sample. The outside the sample bias is therefore likely small. Furthermore, quantity data is available, so that the relative importance of individual items is known. This allows us to calculate superlative indices which take substitution effects into account.

Hedonic regressions using scanner data

Outlet groups

For each type of computer separate hedonic functions were estimated. Before a decision could be made about the functional form of the regressions, which variables to include and whether or not to pool the data across time, the issue of the outlet type has to be resolved. The outlet where a computer is sold, is not a physical characteristic, but it does tend to influence its price. This is because different outlets have different pricing policies and consumers value services offered by different outlets.

A straightforward solution is to pool the data across outlets and add dummy variables for the outlet types. This is a rather awkward solution since it may bias the estimates of the other characteristics. The relation between characteristics and prices may not be the same across outlets, just as it may differ across time.

A better solution would be to condition for the outlet type and estimate separate regressions for each outlet type. There is, however, one big drawback that comes with this solution, i.e. the number of observations is not the same for the different outlet types, and it is very low in some cases. To avoid throwing away observations, the data were pooled across different outlet types. To determine how to group the outlet types the following procedure was used. For each equipment type, the data were pooled across all outlet types and months. Thus nine regressions were carried out for each equipment type, using a different outlet type as the base outlet each time.⁴ If the coefficient of an outlet dummy was not significant, the assumption was made that there is no price differential between

⁴ For servers, only five regressions were run as servers are only sold in five different outlet types.

this outlet type and the base outlet of the regression, and that these outlets can therefore be pooled. For index number purposes, outlet types OER and SH were never pooled with any of the outlet other types, since the former mainly sell to businesses as opposed to the other types.

This procedure led to a subdivision into five, two and three groups for PCs, notebooks and servers respectively. Table 2 gives an overview of the outlet groups. Note that, apart from the distinction between ‘consumer outlets’ and ‘business outlets’, there is no a priori expectation on which outlet types will be similar. Instead it is purely an empirical matter.

Table 2
Division of outlet types into groups

Personal computers					Notebooks		Servers		
1	2	3	4	5	1	2	1	2	3
BUYING	CHAINS	CS	OER	SH	BUYING	OER	CHAINS	OER	SH
	DEPMO								
PRT	H				CHAINS	SH	CS		
TCS	INDEP				CS		INDEP		
					DEPMOH				
					INDEP				
					PRT				
					TCS				

Since the price differentials across outlet types within groups are assumed to be zero, no dummy variables for outlet types were adopted in the remainder of the hedonic regressions except in the case of group 1 for notebooks. Here it was not possible to make a division into smaller groups without resulting in too few observations for some adjacent month regressions.

Choice of variables

Since the number of quality characteristics in the data set is limited, there is not much room for different selections. All variables which are clearly associated with both user value *and* resource costs, were included in the hedonic functions. These include SPEED, HDISK, MEMORY, MONITOR, and USB. For notebooks, SCRSIZE and dummies for the different available screen types were included as well.

In all regressions two sets of dummy variables remain, i.e., those for processor type and those for brand. Both variables are no clear performance indicators, but are proxies for performance. In the case of processors it is well known that the speed in MHZ alone is not a sufficient indicator of its performance. For example, a Pentium processor is considered to be better than a Celeron processor with the same clock speed in MHZ. However, any information on other performance characteristics of

processors is lacking from the data set, so dummies for the type of processor were included in the regressions. Depending on the type of computer and the month, different processor types were chosen as the base type.

The brand of a computer is a more thorny issue. A brand may indicate all kinds of price determining factors, like price mark-ups, unobserved performance characteristics and so on. Because of the proxy character of this type of variable, without clarity about what is actually proxied, there is a case against including them in the regressions. However, they do appear to have explanatory power, so leaving them out would decrease the fit of the model. For this reason, they were included.⁵

Functional form and pooling

Like with the CBS data set, the three main functional forms of hedonic regressions are compared, i.e., the linear, semi-logarithmic and double logarithmic specifications. For the data at hand, the double logarithmic specification proved unsuitable. Some items did not include a hard disk, which implies a value of zero for the relevant characteristic. This makes it inappropriate to take logs. This is especially relevant in the case of servers, for which most items are sold without a hard disk. The goodness-of-fit of both the linear and semi-logarithmic specification was tested for regressions of all ten groups listed in table 2. These regressions pooled the data across all months. In each case the semi-logarithmic specification proved to have the best fit. This specification was therefore chosen for all hedonic regressions.

To reflect the relative importance in sales of the different items all regressions are weighted least squares (WLS). The physical quantity sold was chosen as the weight in the WLS regressions.

For the same reasons as discussed in van Mulligen (2002), the data were pooled for adjacent months, resulting in 36 regressions for each of the ten groups of data. An additional reason is that the number of observations in individual months is still fairly low for some groups despite the aggregation of multiple outlet types. For example, with single-month regressions in the case of servers the number of observations would be lower than the number of explanatory variables in several cases. Pooling data for two adjacent months increases the number of observations and therefore reduces the variance of the regression coefficients.

Summing up, for personal computer the following equation is estimated for each combination of outlet group and adjacent months:⁶

$$\ln p_i = \beta_0 + \beta_1 SPEED_i + \beta_2 HDISK_i + \beta_3 MEMORY_i + \beta_4 MONITOR_i + \beta_5 WORKSTAT_i + \beta_6 USB_i + \sum_{j=1}^{30} \gamma_j PTYPE_{ij} + \sum_{k=1}^{55} \delta_k BRAND_{ik} + \tau T_i + \varepsilon_i \quad (1)$$

⁵ See van Mulligen (forthcoming) for a more detailed discussion of the issue of brands.

⁶ For the sake of simplicity, this equation shows the OLS equation. Actual estimation is carried out with WLS, where the weights are based on the quantity sold of each item. The equations for notebooks and servers are nearly identical, as described above.

Where PTYPE is a dummy for the type of processor of the computer, and BRAND for its brand name. There are 31 different processor types and 56 different brands in the entire database, including generic computers (labelled as 'clones'). Different processor types are chosen as the reference type to omit from the regression. In the case of BRAND, generic computers are always chosen as the reference.

Stability of coefficients

The division of the entire data set into ten outlet groups and thirty-six adjacent month regressions leads to a total of 360 regressions, with up to 41 independent variables in one regression. Listing all coefficients of each regression here would take up a lot of space; interested readers can obtain them from the author. It is noted that the three main physical characteristics, SPEED, HDISK and MEMORY, are significant in most regressions. These regression results are summarised in figures 3 to 5. To save space, only regression coefficients are shown for personal computers, which is by far the largest of the three types in terms of quantity sold.

Although the coefficients of the three characteristics are generally significant, figures 3 to 5 indicate that the coefficients are not constant across outlet groups or time. A downward trend can be witnessed for SPEED and HDISK, and a convergence of the coefficients of the different outlet groups for all three physical characteristics. The downward trend is not surprising, both from a user point of view as from a producer one. The production costs especially of additional units of computation power and hard disk capacity are decreasing at a fast pace, which is reflected in the falling coefficients of these characteristics. On the other hand, buyers' valuation of additional units of these features decreases over time as well because of the fast rate with which computers become more powerful. This is also consistent with the decline in the coefficients of these characteristics. This finding is more or less replicated for notebooks, although the pattern for servers is much more erratic.

Note that the falling coefficients are a consequence of choosing a semi-logarithmic specification. In a double logarithmic specification, the coefficients express the cost and value of additional *percentages* of processor speed, memory size or hard disk capacity. The cost and valuation of percentage rather than unit changes of these features are likely to remain more constant over time.

Figure 3

Coefficients of variable SPEED, adjacent month regressions January 1999/February 1999 to December 2001/January 2002, PCs⁷

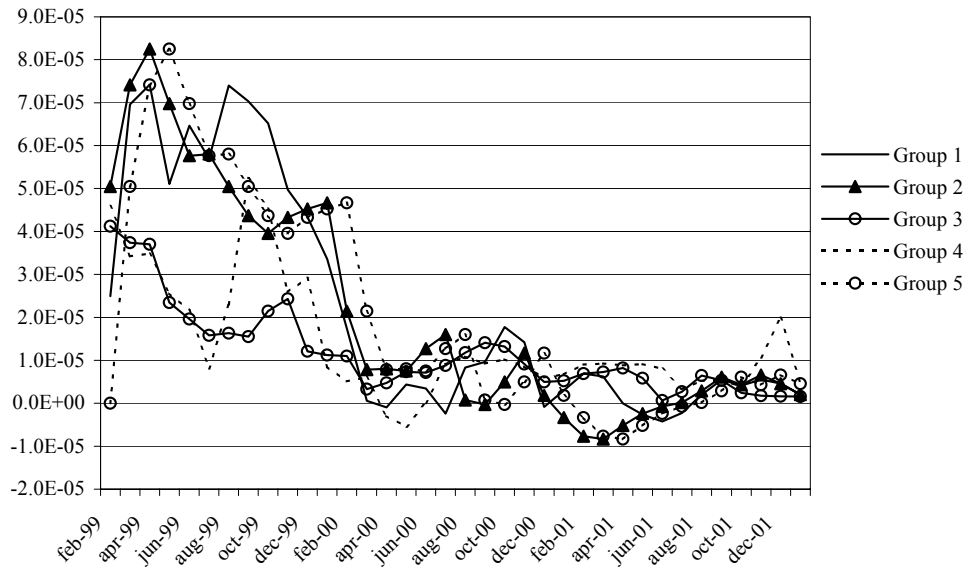
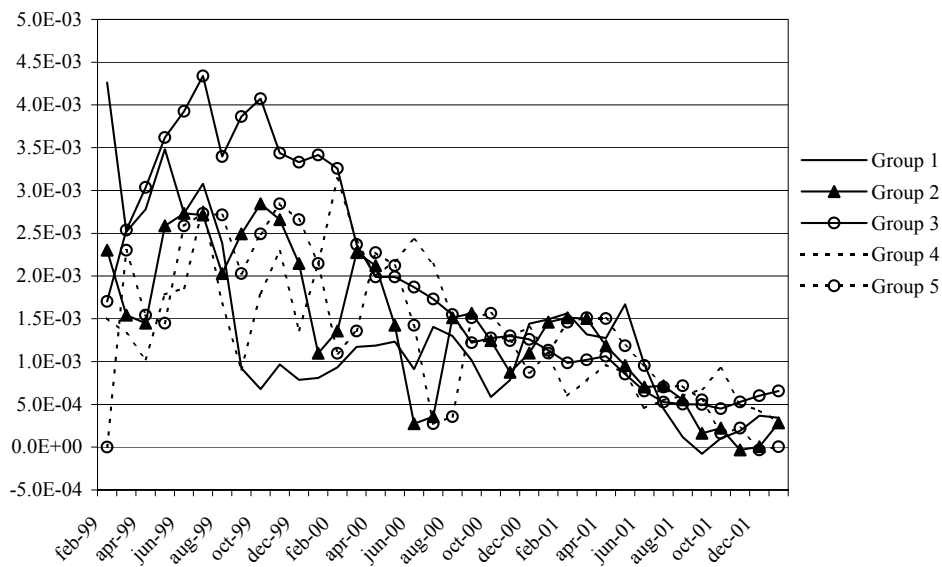


Figure 4

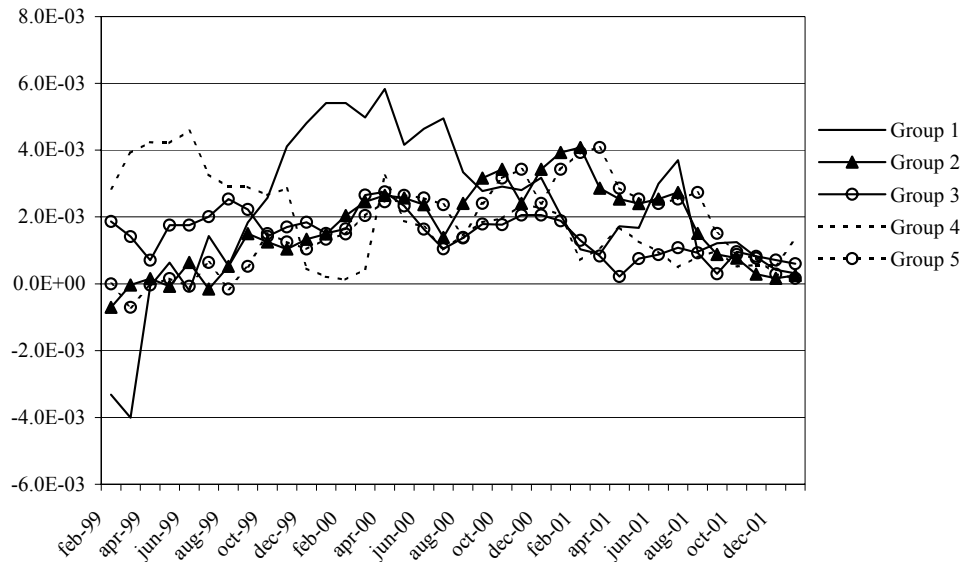
Coefficients of variable HDISK, adjacent month regressions January 1999/February 1999 to December 2001/January 2002, PCs



⁷ Note to figures 3-5: months on the horizontal axis are the second months on the adjacent month regressions

Figure 5

Coefficients of variable MEMORY, adjacent month regressions January 1999/February 1999 to December 2001/January 2002, PCs



Unmeasured variables may also have affected the coefficients of the characteristics above mentioned. In addition, the relatively low number of characteristics seems to have affected explanatory power of the regressions. This is indicated by the low values for R^2 and the high values of the standard error of the regression (SER). The average values for R^2 for the five PC outlet groups across the adjacent month regressions are 0.77, 0.71, 0.65, 0.68, and 0.59, respectively. The averages of the SERs are 0.88, 0.89, 1.32, 1.08 and 2.01, respectively. These figures indicate that the goodness of fit of the regressions is rather mediocre. In many hedonic regressions, especially for computers, R^2 is close to, and not rarely above, 0.9. The high SERs point at a large spread in the data, which is of course the case given the large number of processor and brand dummies.

These regression estimates suggest that pooling the data, even on a bi-monthly basis, is not justified. The reasons that we nevertheless stick to it have a practical nature. Two were already mentioned before: the sometimes low number of observations in single months and the problem of characteristics that are available in one month, but not the adjacent one.

Price indices using scanner data

Matched model indices

The main purpose of this project is to investigate several alternative methods to construct a price index for computers. Since the standard methodology of Statistics Netherlands and other statistical offices is the matched model method, it is only logical that this method is investigated with the present data as well.

The standard approach of most index numbers is to choose a fixed reference period, and to match prices of products in subsequent periods with prices of the same products in the reference period. If old products disappear or new products are introduced on a frequent basis, the odds are that matching like with like gets increasingly difficult as time progresses. This phenomenon is referred to as ‘sample degradation’ and is a major criticism aimed at conventional price index measurement.

A way to get around this problem is to calculate a chained index, resampling and reweighting every period. The case to do this for computers is very strong, as the average lifecycle of individual items is only a few months on average.

Below prices are matched only for item-outlet combinations, i.e., the price of an item was only matched if it was sold at the same outlet type, to prevent outlet price effects from biasing the index. For each outlet type and computer type, matched model indices were calculated both with a fixed reference period (January 1999) and shifting reference periods, where prices in each period were matched with those of one month earlier. The latter results in a chained index.

For each period, the indices of all outlet types were weighted with their relative sales values:

$$P_L^M = \sum_{g=1}^G w_{L,g}^M P_{L,g}^M \quad (2)$$

$$P_P^M = \sum_{g=1}^G w_{P,g}^M P_{P,g}^M \quad (3)$$

with

$$w_{L,g}^M = \frac{\sum_{i=1}^{n_g} p_i^0 q_i^0}{\sum_{g=1}^G \sum_{i=1}^{n_g} p_i^0 q_i^0} \quad (4)$$

$$w_{P,g}^M = \frac{\sum_{i=1}^{n_g} p_i^0 q_i^1}{\sum_{g=1}^G \sum_{i=1}^{n_g} p_i^1 q_i^1} \quad (5)$$

where P_L^M and P_P^M are the Laspeyres and Paasche indices for the matched items of all G outlet types, with respective weights $w_{L,g}^M$ and $w_{P,g}^M$, which are shares in total sales value of matched items in outlet type g .

Laspeyres and Paasche indices with a fixed reference period (with January 1999 as the reference period) and chained weights were calculated. The resulting Fisher indices (the geometric average of Laspeyres and Paasche) are shown in figures 6 to 8. The matching percentages as a share

of total expenditure in the base month (the previous month in the chained case, January 1999 for the fixed weight case) and in the current month, remain relatively constant. The matching percentage of the chained indices for computers is for the entire period on average 81.3% of previous period expenditure share and 78.0% of current month expenditure share on average. For notebooks these average shares are somewhat higher at 87.8% and 84.5% for previous month and current month expenditure share, respectively; for servers they are substantially lower, at 65.0% and 65.1% for previous month and current month respectively.

Figure 6
Matched model indices with fixed reference period and chained weighting,
PCs, all outlet types

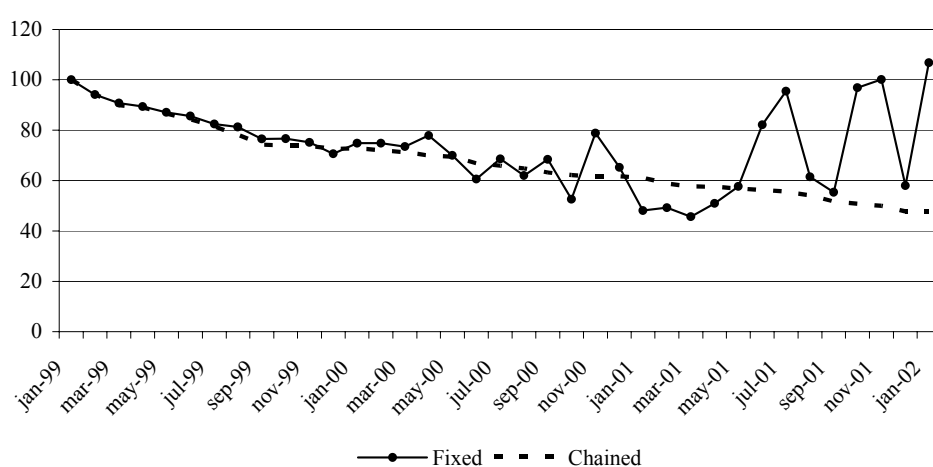


Figure 7
Matched model indices with fixed reference period and chained weighting,
notebooks, all outlet types

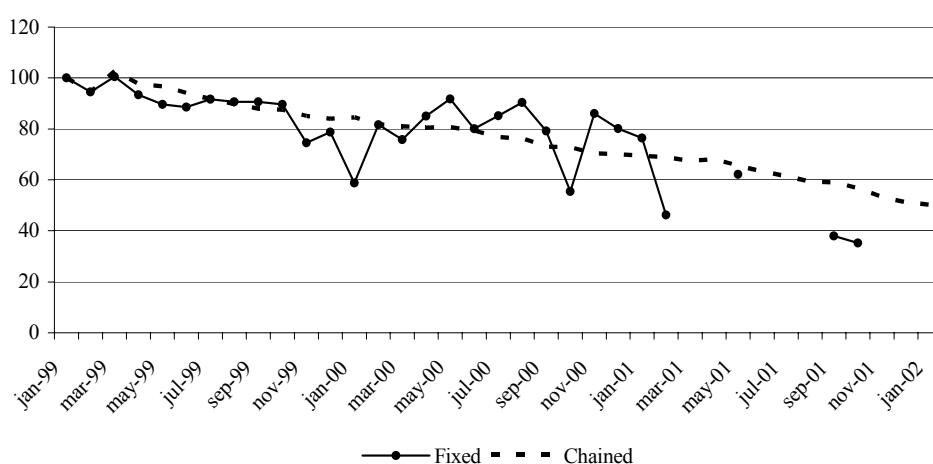
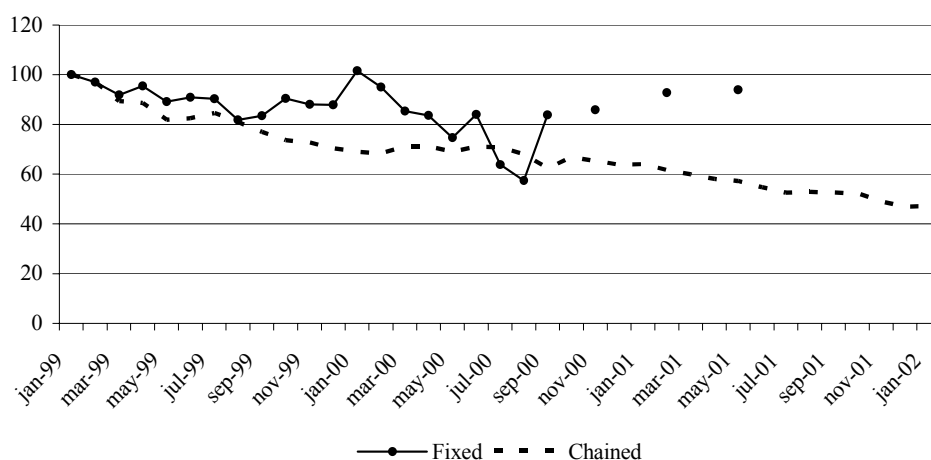


Figure 8
Matched model indices with fixed reference period and chained weighting, servers,
all outlet types



For the fixed period index the number of matched observations declines steadily over time. After three years, there remains not a single item for which prices can be matched with the base period in the case of notebooks and servers. For PCs, the share of items for which a match is still possible after three years is negligible; after one year, the expenditure shares of such items has already declined to 24.7% and 3.0% for base and current month respectively. This means that, as expected, sample degradation appears to be very severe.

All this means that the turnover rate is extremely high in the data set used here. For comparison, Pakes (2002) finds an annual turnover rate for computers in the U.S. of 20%;⁸ Silver and Heravi (2002a) find a similar annual figure in a scanner data set for appliances in the U.K.

As time passes the fixed weight matched index shows an ever more erratic behaviour, which is caused by the decreasing number of items that can be matched. This gives support to those who claim that the matched model method as applied normally at statistical offices fails in the case of computers, since the index weights are held fixed over a too long period of time.

Hedonic indices

Using the hedonic regression results, three hedonic indices are calculated for each type of equipment: a dummy index and two different imputation indices. A hedonic quality adjustment index is not calculated here, as it is very close to a traditional hedonic imputed index. The time consuming task of calculating such an index is probably not worth the effort.

The hedonic dummy indices that are presented here are chained indices using antilogs of the coefficients of the time dummies of the adjacent month regressions. This is a fixed weight index, since observations are not weighted by their relative shares in sales. The regression results are based

⁸ Note that this is a percentage of the number of observations rather than total sales.

on weighted least squares regressions, where quantities are used as weights. Weights are therefore used only implicitly.

Indices based on the imputation method are analysed here in a bit more detail. Missing prices are estimated with a hedonic function and these prices are matched with actual prices. This procedure has its drawback, however, when the explanatory power of the hedonic regression is low. The regressions calculated here show relatively low values for R^2 , and given the presence of quite a few unobserved variables, the coefficients of the observed variables are likely to be biased. This can have major implications for the residuals of actual prices. If residuals are biased, then the matching of actual with estimated prices will take over this bias. To prevent the residuals from entering the index, actual prices can be replaced with fitted estimated prices as well. This procedure is known as ‘double imputation’ (De Haan and Opperdoes, 2002). The results presented here include both traditional, ‘single imputed’, and double imputed hedonic indices.

As I am estimating adjacent month regressions rather than single month regressions, the ratio of estimated prices in the double imputed index equals the antilog of the coefficient τ of the time dummy in equation (1), and makes no direct use of the coefficients of the other explanatory variables. The hedonic double imputed Laspeyres and Paasche indices can be written as:

$$P_L = w^{0M} P_L^M + (1 - w^{0M}) e^{\hat{\tau}} \quad (6)$$

$$P_P = \left[\frac{w^{1M}}{P_P^M} + \frac{(1 - w^{1M})}{e^{\hat{\tau}}} \right]^{-1} \quad (7)$$

where w^{0M} and $(1 - w^{0M})$ are the base month expenditure shares of matched and disappearing items, respectively; w^{1M} and $(1 - w^{1M})$ are current month expenditure shares of matched and new items. P_L^M and P_P^M are Laspeyres and Paasche indices for matched items only. The double imputed hedonic indices are therefore weighted averages of matched model indices and hedonic dummy indices.

The double imputation hedonic method is somewhat related to the IP-IQ method described in Triplett (forthcoming), as the price change for new and old models is set equal to the overall price change of all models. It will therefore lie closer to a matched model index than a single imputed hedonic index.

Following De Haan and Opperdoes (2002), the Fisher index, which is the geometric average of the Laspeyres and Paasche indices, can be rewritten in the following way:

$$P_F = (P_L P_P)^{1/2} \quad \Leftrightarrow$$

$$P_F = \left(\frac{P_L}{P_L^M} P_L^M \frac{P_P}{P_P^M} P_P^M \right)^{\frac{1}{2}} \quad \Leftrightarrow$$

$$P_F = \left(\frac{P_L}{P_L^M} \right)^{\frac{1}{2}} \left(\frac{P_P}{P_P^M} \right)^{\frac{1}{2}} (P_L^M P_P^M)^{\frac{1}{2}} \quad (8)$$

Next, define:

$$\lambda = \left(\frac{P_L}{P_L^M} \right)^{\frac{1}{2}}$$

$$\pi = \left(\frac{P_P}{P_P^M} \right)^{\frac{1}{2}}$$

and rewrite (8) as:

$$P_F = \lambda \pi P_F^M \quad (9)$$

where $P_F^M = (P_L^M P_P^M)^{\frac{1}{2}}$ is the Fisher index of matched items only.

The factors λ and π can be interpreted as the effects of disappeared items on the Laspeyres index and new items on the Paasche index respectively. If the shares of disappearing and new items are small (i.e. w^{OM} and w^{IM} are close to one), then P_F^M is a close approximation of P_F . This is true in the case of two periods, but if the Fisher indices are combined into a chained index, small differences between P_F^M and P_F can have substantial effects in the long run (like, say, thirty-six periods).

However, we cannot say a priori whether P_F^M will overstate or understate P_F . This depends on the net effect of λ and π combined. Whether $\lambda\pi > 1$ or $\lambda\pi < 1$ is an empirical matter, and will be investigated here. However, economic theory may provide some insight in the sizes of λ and π . In a competitive and transparent market, where consumers have full information, we expect to find that the Laspeyres price index of matched items is smaller than the index of disappearing items, and so $\lambda > 1$. Demand for disappeared items has fallen to zero, which may be caused by their obsolescence. This may imply that the imputed prices of these items are too high as compared to items with continued sales. On the other hand, retailers sometimes offer old computer models at discount prices to clear

shelves, and make room for newer models.⁹ If this effect is stronger, this will result in a value of $\lambda < 1$.

Likewise, the economics of new goods implies that new models are likely to have high base period prices, had they been available. In this respect the concept of Hicks' reservation price is sometimes put forward. This is the price that sets the demand for a product just equal to zero (Hicks, 1940; Triplett, forthcoming). Imputed prices of new goods are therefore likely to be 'too low' as compared to items that were available previously (i.e. lower than the reservation price). This leads to the expectation that the Paasche index of matched items is larger than the index of new items, and so $\pi < 1$. But the effect of new models can also go in the other direction. When introduced, prices of new computers sometimes contain a premium, which is based on their newness and exclusiveness, leading to a value of π which is greater than 1.

Table 3
Average monthly price changes for different indices and effects of old and new models, January 1999 - January 2002, all equipment types

Price change:	PCs	Notebooks	Servers
Matched model	-2.0	-1.9	-2.1
Hedonic dummy	-3.2	-2.4	-2.6
Hedonic single imputed	-2.5	-2.2	-2.4
Hedonic double imputed	-2.3	-2.0	-2.3
Effect of old models: ^a			
Hedonic single imputed	-0.5	-0.2	-1.0
Hedonic double imputed	-0.1	-0.1	-0.1
Effect of new models: ^b			
Hedonic single imputed	0.0	-0.1	0.6
Hedonic double imputed	-0.1	0.0	-0.2

^a: Equals $(\lambda - 1) * 100$

^b: Equals $(\pi - 1) * 100$

Before I turn to the comparison between the CPI and the price indices based on the scanner data, I first pay some attention to the differences between the matched model indices and hedonic indices that were estimated with the GfK data set. For all three types of computer equipment, four

⁹ If discounts take place, their effects should appear in the time dummy when adjacent period regressions are estimated, as discounts are a pure deflationary effect.

indices are calculated for each outlet group: a matched model index, a hedonic dummy index (based on the time dummies from the adjacent month regressions) and two hedonic imputation indices (based on the imputation methods described above). In all cases, bimonthly Fisher indices were chained over the entire period. The indices from the individual outlet types were aggregated with the expenditure shares of the outlet types to derive aggregate indices for the three types of computer equipment.¹⁰ The resulting indices are represented in figures 9 to 11. To conserve space, table 3 only shows the average monthly price changes of all indices, including the average effects of old and new items. Monthly indices are available from the author.

Figure 9
Hedonic and matched model Fisher indices for PCs, the Netherlands,
all outlets, January 1999 = 100

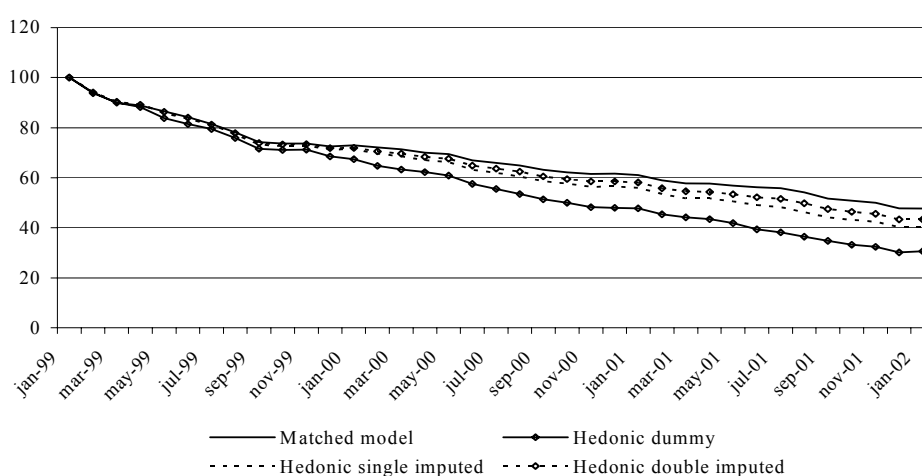
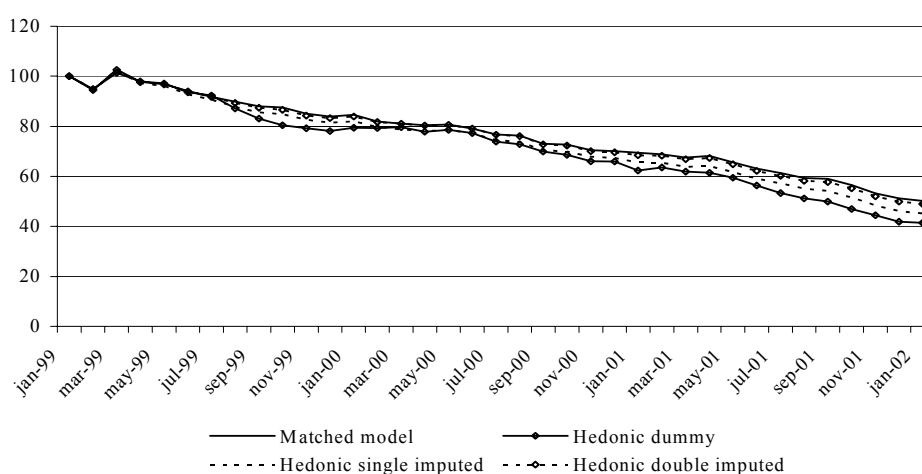
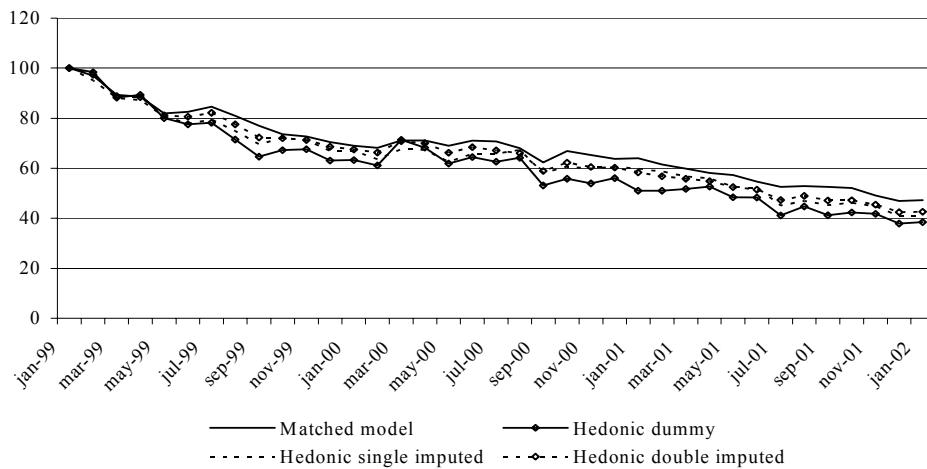


Figure 10
Hedonic and matched model Fisher indices for notebooks, the Netherlands,
all outlets, January 1999 = 100



¹⁰ Also the hedonic dummy indices were aggregated across outlets using expenditure shares, although the individual dummy indices for the different outlets are unweighted indices.

Figure 11
Hedonic and matched model Fisher indices for servers, The Netherlands,
all outlets, January 1999 = 100



The fact that the matched model indices are above the hedonic indices is not surprising on theoretical grounds. The current matched model procedure leaves out unmatched observations, and therefore implicitly assumes that the price change of unmatched items equals the price change of matched items. As discussed by Triplett (forthcoming), this ‘imputed price change, implicit quality adjustment’ (IP-IQ) method will introduce an upward bias in the price index if prices are falling, which is the case here. These results are in line with Barzyk and MacDonald (2002) and Evans and Scherrer (2002).

The differences between the hedonic imputed indices and the matched model indices are relatively small on a month-to-month basis. The differences are larger for PCs than for notebooks and servers. As expected, the single imputed hedonic index is below the double imputed hedonic index. The dummy index is in all cases below the other three. This reflects the importance of using weights in indices. As all regressions are WLS with quantities as weights, the dummy index is only implicitly weighted. The other indices use expenditure shares as weights in a Laspeyres-Paasche-Fisher framework, and therefore make proper use of weights. The lower dummy index suggests that computers with a rapid price decline are over-represented in the dummy index. This is confirmed when unweighted versions of the other three indices are computed. Although not shown here, the unweighted matched model indices are substantially below the weighted matched model, and the unweighted hedonic imputed indices nearly coincide with the hedonic dummy indices. Given the differences between the several indices shown in table 3, one can conclude that the effect of weighting (the difference between the hedonic imputed indices and the dummy indices) is roughly equal to or exceeds the effect of using hedonics or not (the difference between the hedonic imputed indices and the matched model index). Note that both effects are in a different direction. Both effects, however, pale in comparison to the effect of using a chained principle with shifting reference periods rather than a fixed base period, as shown in Figures 6 to 8.

A large share of matched items can explain the similarity between the hedonic imputed indices on the one hand and the matched model index on the other. In such a case, the effect of old and new items will be minimal. However, in the current data base, 15-35% of all observations is not matched, a substantial amount. This suggests that matched items give a reasonable representation of

the entire market, although this conclusion is somewhat weaker for personal computers than for notebooks and servers.

In all cases but one, the separate effects of old and new items is negative, and both effects are usually small. These effects are of course larger in an absolute sense for the single imputed hedonic indices, as the price change of the new and old items in the double imputed hedonic index is imputed from all computers rather than just old and new ones. The results of the single imputed hedonic index for servers are somewhat different. The effects of new and old items are relatively large, but of opposite sign. This may be caused by the distinct properties of servers, which serve different purposes than personal computers and notebooks. The difference between the matched model index and the single imputed hedonic index is nearly entirely caused by computers that exit from the market. A likely explanation is that old and obsolescent computers are dumped for bargain prices to clear shelves.

Although the month-to-month differences between the indices are small in most cases, these differences cumulate to larger gaps over longer periods of time. This may justify using hedonic methods, especially for PCs, although their benefit is dwarfed by that of using a chained index.

A reason for concern is the low explanatory power of the hedonic regressions that are estimated with (1). No information on a number of possible important characteristics is available, which results in collinear coefficients of the included variables, a bad fit, and a large variance of the time dummy coefficients. A better data set with more quality characteristics might increase the significance of the difference between a matched model index and a hedonic imputed index. However, it is not clear whether such a data base exists for computers as yet. Alternative large data sets, such as those used by Barzyk and MacDonald (2002) and Evans and Scherrer (2002), which contain a lot more information on quality characteristics, are based on manufacturer catalogues, and do not provide information on sales data. Such data sets may be used to test the difference between unweighted matched model indices and hedonic imputed indices, but not for superlative indices which include sales data.

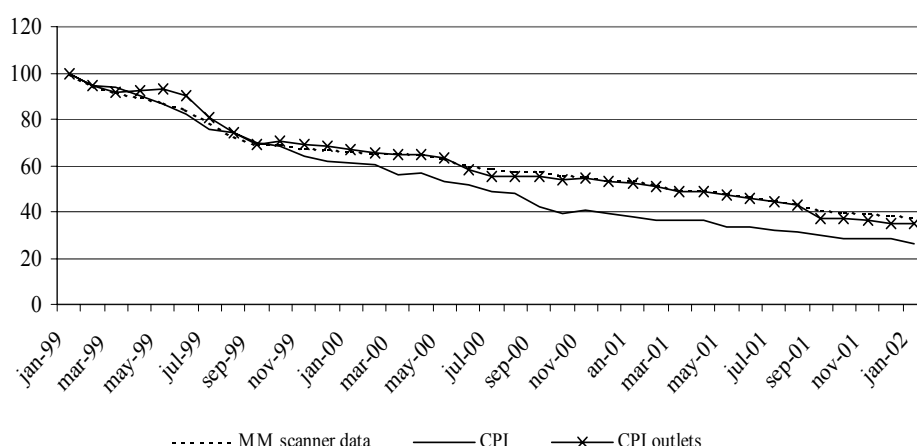
Confrontation with the CPI

The indices that were shown above are aggregates of all outlet groups, both business-to-consumer and business-to-business outlet types. In the remainder of this section, a distinction will be made between these two types. Since the CPI, which contains only PCs, by definition only applies to sales to private consumers, only price indices which apply to ‘consumer outlets’ will be compared with the CPI. For PCs, these are the outlets in groups 1 to 3, for both notebooks and servers these are the outlets in the respective groups 1 (see table 3).

Figure 12 compares the official CPI with the matched model index for PCs based on the scanner data set (consumer outlets only). It appears that the observations in the CPI are nearly all from one particular outlet type of the seven types that mainly sell to consumers. This outlet type can be identified in the GfK data base.¹¹ The matched model index of this outlet type only (labelled ‘CPI outlets’) is shown in figure 12 as well. The official CPI is about ten percentage points below the other

two indices based on scanner data. This is a substantial difference if one takes into account that the CPI is at 26.2 in the final period of the analysis (January 2002). The average monthly price change of the CPI is -3.7%, for the matched model index based on all scanner data this is -2.7%; the average monthly price change in ‘CPI outlets’ only is -2.9%.

Figure 12
Official CPI for computers vs. scanner data matched model indices, the Netherlands, all consumer outlets and ‘CPI outlets’, January 1999 = 100



This gap between the CPI and the scanner data indices of nearly one percentage point *per month* is a very large difference. If we consider the matched model index using the scanner data for all consumer outlets as the ‘true’ price index for computers in the Netherlands, the Dutch CPI for computers contains a substantial *downward* bias, contrary to popular belief concerning official price index numbers for computer equipment. This bias may be attributed to three different factors: methodology, sampling and weighting.

The method that is used to construct the CPI cannot explain the large difference. The CPI is calculated with a matched model methodology, where only identical computers are matched, similar to how the matched model index on the scanner data set was constructed.

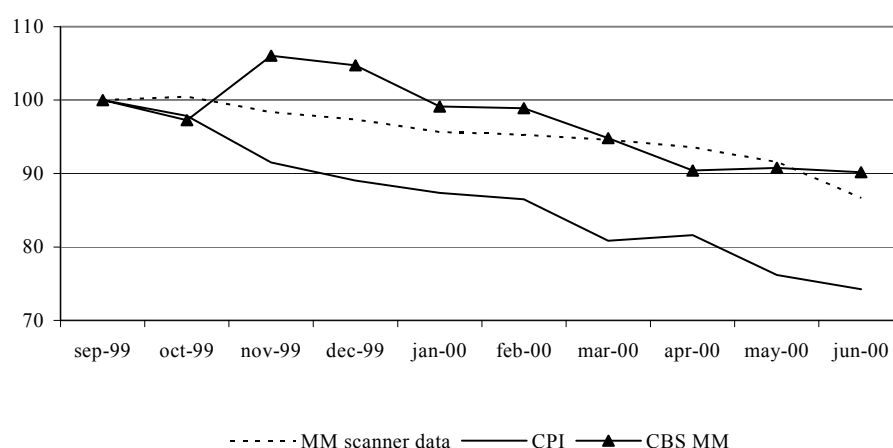
Sampling and weighting issues are more likely candidates for the widening gap between the matched model indices and the CPI. The CPI contains only several dozen observations each month, and this number is even in decline. Although the type of outlets that are observed for the CPI constitutes a modest share of all computer sales in the Netherlands, the price index of this outlet type is rather similar to the overall price index based on scanner data. This suggests that the type of outlet from which observations are taken for the CPI is a reasonable representation of the Dutch PC market, but that the sampling within this outlet can be improved. Additionally each computer is given the same weight in the index. This is a second drawback of the official index, but one that is actually

¹¹ For confidentiality reasons, the actual outlet type is not disclosed here.

standard practice in CPI measurement, namely that at the level of price collection of individual items, which together comprise ‘basic headings’, no weighting scheme is applied. This can explain a large part of the difference between the CPI and the matched model index on the scanner data set.

This conclusion concerning sampling and weighting is confirmed when we compare the results of the scanner data analysis with those of the exercise using the CBS data base. Figure 13 combines three indices from van Mulligen (2002) and figure 12, for the period where all three are known (September 1999 – June 2000): the official CPI, the (unweighted) matched model index using the entire CBS data base on computer prices, and the (expenditure weighted) matched model index using the scanner data set for all consumer outlets (the ‘true’ matched model index).

Figure 13
Official CPI for computers vs. matched model indices using the CBS and scanner data bases,
the Netherlands, September 1999 = 100



The unweighted matched model index based on the CBS data set (labelled ‘CBS MM’), which uses more observations than the CPI, appears to lie closer to the ‘true’ index than the official CPI. However, this is to a large extent caused by the strange behaviour of the CBS MM index in October-November 1999. Excluding this period, both indices based on the CBS data set on average differ from the ‘true’ index by about the same amount. This suggests that simply extending the official CPI with observations that are presently not used provides no quick solution to the downward bias in the CPI. Drawing a better sample of computers, possibly including sales data, therefore still seems necessary.

4. Summary

A detailed analysis on the dataset that is used by Statistics Netherlands to construct the CPI for computers (van Mulligen, 2002) revealed that the differences between a matched model index and hedonic indices on this dataset are fairly small. This result seems to indicate that for this data set, traditional matched model indices introduce no or only a small bias in the price index for computers. The same conclusion was reached with the use of a scanner data set, the result of which are presented

in this paper, although there are substantial differences between the matched model indices using either data set.

Therefore, it seems that the largest drawback of the indices (both hedonic and matched model) calculated with the data collected by CBS is the data set itself. The first flaw of the data is that weights are not provided. No information on the sales volume is given for the models in the sample, so that popular items and infrequently sold configurations are treated equally. But since index number construction at the lowest level of aggregation is usually unweighted, one could direct this criticism at the entire CPI. A second point of concern is that the sample for the CPI can be improved, even though the scanner data set suggests that the type of outlets that is used in the CPI sample seems rather representative for the entire computer market in the Netherlands. Together these two flaws lead to a substantial difference of about one percentage point per month between the official CPI and a matched model index based on a scanner data set. Since the scanner data set used here contain virtually all computer sales in the Netherlands, we can assume that a price index for this data set equals the actual matched model price index for computers, and that therefore the CPI has a downward bias of one percentage point per month, barring quality biases.

The difference between matched model indices and hedonic (imputed) indices is less clear cut. On the one hand, these are smaller than sometimes is found. On the other hand, the differences may be small, but they are not insubstantial. Concerning hedonic indices, a reasonable conclusion based on the results found in this paper would be that if data on characteristics is available, hedonic methods should be pursued, and the differences between hedonic indices and matched model indices should be evaluated. The fact that these differences are modest in the case of computers, a product with a fast rate of quality change, might indicate that for other products with slower quality changes the differences between both basic methods are negligible. But this is not a forgone conclusion, and needs to be determined empirically.

The results presented here point out that a more important point than the question of using hedonics or not is that of using a chained index principle rather than a fixed base. The resampling may not be necessary on a monthly basis for every product, but holding the reference period fixed for several years is definitively not an option. Furthermore, efforts should be made to draw a good sample, if possible with sales information. The chained index principle is already employed in the Dutch CPI for computers, but this is not the case everywhere and for each product.

The advantage of a high frequency matched model index compared with the hedonic method is that price statisticians are very familiar with the matched model procedure. Furthermore, although no *explicit* quality adjustment is carried out with this methodology, it entails an *implicit* quality adjustment. This again calls for attention with respect to the sampling of observations, so that the possible outside the sample bias caused by the class mean method remains minimal. However, when a good sample is drawn with the purpose for constructing a high frequency matched model index, a hedonic index is usually possible as well. After all, information on characteristics is used for the matching of observations, and this information may as well be used for hedonic regressions.

Summing up, the main conclusion of this paper is that for the construction good and unbiased price indices for computers or in fact for any other product, using a chained index principle with frequent resampling is absolutely necessary. Using information on expenditure shares, or hedonic

methods to make explicit quality adjustments can provide even better estimates of price change, but this is of less immediate importance.

Having said that, a point has to be made concerning the relevance of research into price indices for computers. In private conversations with statisticians, it has been argued that a lot of fuss has been made about these price indices, whereas the ultimate share of computers in the total CPI is small. In the Netherlands the weight of computers in the CPI is less than 0.4%, so biases in the price index for computers are hardly reflected in the total CPI. A similar point can probably be made for other countries.

But this is not true for computers as investment goods, where their share is much bigger than in the CPI. The present paper only studied consumer price indices, but of course the quality problem in computers is no less relevant in producer price indices or output deflators. When output deflators for computers are not adjusted for quality change, implicitly or explicitly, real output measures of computer producing and real productivity measures of computer using industries are seriously defunct, as brought forward by Wyckoff (1995), who compared different deflators for computer equipment across the OECD. A practical problem with output deflators and producer price indices lies in the fact that sufficient data can be harder to obtain than for consumer prices, although the experiences of the U.S. statistical agencies point out that it can actually be done.

Looking at the relevance of this research in the case of consumer prices, it can be stated that this lies in the nature of computers: quality change in this commodity type is very fast, probably the fastest in any type of durable good. Necessary conditions for the correctness of a matched model index are that sampling is done on a frequent basis, and that price indices are chained and do not refer to a fixed base period. Based on the research presented here, for computers, monthly sampling and chaining go a long way to provide better estimates of actual price change. Taking into account the difference between hedonic and matched model indices presented here, this may not be sufficient when there is (rapid) quality change. The challenge for statistical offices to collect good data and compare hedonic with matched model indices remains.

References

- Aizcorbe, A, C. Corrado and M. Doms (2000), *Constructing price and quantity indexes for high technology goods*, Federal Reserve Board, Washington
- Barzyk, F. and M. MacDonald (2002), *The treatment of quality change for computer price indexes – A review of current and proposed practices*. Paper presented at the conference on Price Indices and the Measurement of Quality Changes, ZEW, Mannheim, 25-26 April 2002
- Boskin, M.J., E.R. Dulberger, R.J. Gordon, Z. Griliches and D.W. Jorgenson (1996), *Toward a more accurate measure of the cost of living*, Advisory Commission to study the Consumer Price Index. Interim report to the Senate Finance Committee, December 4
- Dalén, J. (2002), *Personal computers in different HICPs*. Paper presented at the Workshop on Economic Measurement: Hedonic Indexes: Too Fast? Too Slow? Or Just Right?, Brookings Institution, Washington, D.C., 1 February 2002
- Deutsche Bundesbank (2000), *Monthly Report August 2000*, Frankfurt am Main
- Elfering, S. (2001) *Procesbeschrijving van het consumentprijsindexcijfer en het producentenprijsindexcijfer*, mimeo, Statistics Netherlands, Voorburg (in Dutch)
- Evans, R. and P. Scherrer (2002), *Hedonic methods for computers in industrial price statistics: The French experience*. Paper presented at the conference on Price Indices and the Measurement of Quality Changes, ZEW, Mannheim, 25-26 April 2002
- de Haan, J. (2002), *On the time dummy approach to hedonic modelling*, mimeo, Statistics Netherlands, Voorburg
- de Haan, J. and E. Opperdoes (2002), *Hedonic and matched model Fisher price indices for cars*, Working paper, Statistics Netherlands, Voorburg
- Heravi, S, A. Heston and M. Silver (2003), “Using scanner data to estimate country price parities: A Hedonic Regression Approach”. , *Review of Income and Wealth*, vol. 49, no. 1, pp. 1-21
- Hicks, J. R. (1940), “The Valuation of the Social Income” *Economica* N.S.vol. 7, no. 2, pp. 105-124
- Ioannidis, C. and M. Silver (1999), “Estimating Hedonic Indices: An Application to UK Television Sets”, *Journal of Economics, Zeitschrift für Nationalökonomie*, vol. 69, no. 1, pp. 71-94
- van Mulligen, P.H. (2002), *A new Dutch Consumer Price Index for computers: some first results using the CPI database*, Working paper, Statistics Netherlands, Voorburg
- van Mulligen, P.H. (2003), *Quality aspects in price indices and international comparisons: Applications of the hedonic method*, Ph.D. thesis, Statistics Netherlands, Voorburg
- Pakes, A. (2002), *A reconsideration of hedonic price indices with an application to PCs*. Paper presented at the Workshop on Economic Measurement: Hedonic Indexes: Too Fast? Too Slow? Or Just Right?, Brookings Institution, Washington, D.C., 1 February 2002
- Schreyer, P. (2002), “Computer price indices and international growth and productivity comparisons”, *Review of Income and Wealth*, vol. 48(1), pp. 15-32

- Silver, M. and S. Heravi (2001), “Scanner data and the measurement of inflation”, *The Economic Journal*, June, pp 384-405
- Silver, M. and Heravi, S. (2002a), “The Measurement of Quality-Adjusted Price Changes”, in M. Shapiro and R. Feenstra (eds.), *Scanner Data and Price Indexes*, National Bureau of Economic Research, Studies in Income and Wealth, vol. 61, University of Chicago Press, Chicago
- Silver, M. and Heravi, S. (2002b), “Why the CPI Matched Models Method May Fail Us: Results from an Hedonic and Matched Experiment Using Scanner Data”, *European Central Bank Working Paper No. 144*, Frankfurt
- Summers, R. (1973), “International comparisons based upon incomplete data”, *Review of Income and Wealth*, vol 19, March, pp. 1-16
- Triplett, J.E. (forthcoming), *Handbook on quality adjustment of price indexes for information and communication technology products*, draft, OECD, Paris
- Wyckoff, A.W. (1995), “The impact of computer prices on international comparisons of labour productivity”, *Economics of Innovation and New Technology*, vol. 3, pp 277-293

Papers issued in the series of the Groningen Growth and Development Centre

Papers marked * are also available in pdf-format on the internet: <http://www.eco.rug.nl/ggdc/>

- 536 (GD-1) Maddison, Angus and Harry van Ooststroom, The International Comparison of Value Added, Productivity and Purchasing Power Parities in Agriculture (1993)
- 537 (GD-2) Mulder, Nanno and Angus Maddison, The International Comparison of Performance in Distribution: Value Added, Labour Productivity and PPPs in Mexican and US Wholesale and Retail Trade 1975/7 (1993)
- 538 (GD-3) Szirmai, Adam, Comparative Performance in Indonesian Manufacturing, 1975-90 (1993)
- 549 (GD-4) de Jong, Herman J., Prices, Real Value Added and Productivity in Dutch Manufacturing, 1921-1960 (1993)
- 550 (GD-5) Beintema, Nienke and Bart van Ark, Comparative Productivity in East and West German Manufacturing before Reunification (1993)
- 567 (GD-6)* Maddison, Angus and Bart van Ark, The International Comparison of Real Product and Productivity (1994)
- 568 (GD-7) de Jong, Gjalt, An International Comparison of Real Output and Labour Productivity in Manufacturing in Ecuador and the United States, 1980 (1994)
- 569 (GD-8) van Ark, Bart and Angus Maddison, An International Comparison of Real Output, Purchasing Power and Labour Productivity in Manufacturing Industries: Brazil, Mexico and the USA in 1975 (1994) (second edition)
- 570 (GD-9) Maddison, Angus, Standardised Estimates of Fixed Capital Stock: A Six Country Comparison (1994)
- 571 (GD-10) van Ark, Bart and Remco D.J. Kouwenhoven, Productivity in French Manufacturing: An International Comparative Perspective (1994)
- 572 (GD-11) Gersbach, Hans and Bart van Ark, Micro Foundations for International Productivity Comparisons (1994)
- 573 (GD-12) Albers, Ronald, Adrian Clemens and Peter Groote, Can Growth Theory Contribute to Our Understanding of Nineteenth Century Economic Dynamics (1994)
- 574 (GD-13) de Jong, Herman J. and Ronald Albers, Industrial Output and Labour Productivity in the Netherlands, 1913-1929: Some Neglected Issues (1994)
- 575 (GD-14) Mulder, Nanno, New Perspectives on Service Output and Productivity: A Comparison of French and US Productivity in Transport, Communications Wholesale and Retail Trade (1994)
- 576 (GD-15) Maddison, Angus, Economic Growth and Standards of Living in the Twentieth Century (1994)

- 577 (GD-16) Gales, Ben, In Foreign Parts: Free-Standing Companies in the Netherlands around the First World War (1994)
- 578 (GD-17) Mulder, Nanno, Output and Productivity in Brazilian Distribution: A Comparative View (1994)
- 579 (GD-18) Mulder, Nanno, Transport and Communication in Mexico and the United States: Value Added, Purchasing Power Parities and Productivity (1994)
- 580 (GD-19) Mulder, Nanno, Transport and Communications Output and Productivity in Brazil and the USA, 1950-1990 (1995)
- 581 (GD-20) Szirmai, Adam and Ren Ruoen, China's Manufacturing Performance in Comparative Perspective, 1980-1992 (1995)
- GD-21 Fremdling, Rainer, Anglo-German Rivalry on Coal Markets in France, the Netherlands and Germany, 1850-1913 (December 1995)
- GD-22 Tassenaar, Vincent, Regional Differences in Standard of Living in the Netherlands, 1800-1875. A Study Based on Anthropometric Data (December 1995)
- GD-23 van Ark, Bart, Sectoral Growth Accounting and Structural Change in Postwar Europe (December 1995)
- GD-24 Groote, Peter, Jan Jacobs and Jan Egbert Sturm, Output Responses to Infrastructure in the Netherlands, 1850-1913 (December 1995)
- GD-25* Groote, Peter, Ronald Albers and Herman de Jong, A Standardised Time Series of the Stock of Fixed Capital in the Netherlands, 1900-1995 (May 1996)
- GD-26 van Ark, Bart and Herman de Jong, Accounting for Economic Growth in the Netherlands since 1913 (May 1996)
- GD-27* Maddison, Angus and D.S. Prasada Rao, A Generalized Approach to International Comparisons of Agricultural Output and Productivity (May 1996)
- GD-28 van Ark, Bart, Issues in Measurement and International Comparison of Productivity - An Overview (May 1996)
- GD-29* Kouwenhoven, Remco, A Comparison of Soviet and US Industrial Performance, 1928-90 (May 1996)
- GD-30 Fremdling, Rainer, Industrial Revolution and Scientific and Technological Progress (December 1996)
- GD-31 Timmer, Marcel, On the Reliability of Unit Value Ratios in International Comparisons (December 1996)
- GD-32 de Jong, Gjalt, Canada's Post-War Manufacturing Performance: A Comparison with the United States (December 1996)
- GD-33 Lindlar, Ludger, "1968" and the German Economy (January 1997)
- GD-34 Albers, Ronald, Human Capital and Economic Growth: Operationalising Growth Theory, with Special Reference to The Netherlands in the 19th Century (June 1997)

- GD-35 Brinkman, Henk-Jan, J.W. Drukker and Brigitte Slot, GDP per Capita and the Biological Standard of Living in Contemporary Developing Countries (June 1997)
- GD-36 de Jong, Herman, and Antoon Soete, Comparative Productivity and Structural Change in Belgian and Dutch Manufacturing, 1937-1987 (June 1997)
- GD-37 Timmer, M.P., and A. Szirmai, Growth and Divergence in Manufacturing Performance in South and East Asia (June 1997)
- GD-38* van Ark, B., and J. de Haan, The Delta-Model Revisited: Recent Trends in the Structural Performance of the Dutch Economy (December 1997)
- GD-39* van der Eng, P., Economics Benefits from Colonial Assets: The Case of the Netherlands and Indonesia, 1870-1958 (June 1998)
- GD-40* Timmer, Marcel P., Catch Up Patterns in Newly Industrializing Countries. An International Comparison of Manufacturing Productivity in Taiwan, 1961-1993 (July 1998)
- GD-41* van Ark, Bart, Economic Growth and Labour Productivity in Europe: Half a Century of East-West Comparisons (October 1999)
- GD-42* Smits, Jan Pieter, Herman de Jong and Bart van Ark, Three Phases of Dutch Economic Growth and Technological Change, 1815-1997 (October 1999)
- GD-43* Fremdling, Rainer, Historical Precedents of Global Markets (October 1999)
- GD-44* van Ark, Bart, Lourens Broersma and Gjalt de Jong, Innovation in Services. Overview of Data Sources and Analytical Structures (October 1999)
- GD-45* Broersma, Lourens and Robert McGuckin, The Impact of Computers on Productivity in the Trade Sector: Explorations with Dutch Microdata (October 1999, Revised version June 2000)
- GD-46* Sleifer, Jaap, Separated Unity: The East and West German Industrial Sector in 1936 (November 1999)
- GD-47* Rao, D.S. Prasada and Marcel Timmer, Multilateralisation of Manufacturing Sector Comparisons: Issues, Methods and Empirical Results (July 2000)
- GD-48* Vikström, Peter, Long term Patterns in Swedish Growth and Structural Change, 1870-1990 (July 2001)
- GD-49* Wu, Harry X., Comparative labour productivity performance in Chinese manufacturing, 1952-1997: An ICOP PPP Approach (July 2001)
- GD-50* Monnikhof, Erik and Bart van Ark, New Estimates of Labour Productivity in the Manufacturing Sectors of Czech Republic, Hungary and Poland, 1996 (January 2002)
- GD-51* van Ark, Bart, Robert Inklaar and Marcel Timmer, The Canada-US Manufacturing Gap Revisited: New ICOP Results (January 2002)
- GD-52* Mulder, Nanno, Sylvie Montout and Luis Peres Lopes, Brazil and Mexico's Manufacturing Performance in International Perspective, 1970-98 (January 2002)

- GD-53* Szirmai, Adam, Francis Yamfwa and Chibwe Lwamba, *Zambian Manufacturing Performance in Comparative Perspective* (January 2002)
- GD-54* Fremdling, Rainer, *European Railways 1825-2001, an Overview* (August 2002)
- GD-55* Fremdling, Rainer, *Foreign Trade-Transfer-Adaptation: The British Iron Making Technology on the Continent (Belgium and France)* (August 2002)
- GD-56* van Ark, Bart, Johanna Melka, Nanno Mulder, Marcel Timmer and Gerard Ypma, *ICT Investments and Growth Accounts for the European Union 1980-2000* (September 2002)
- GD-57* Sleifer, Jaap, *A Benchmark Comparison of East and West German Industrial Labour Productivity in 1954* (October 2002)
- GD-58* van Dijk, Michiel, *South African Manufacturing Performance in International Perspective, 1970-1999* (November 2002)
- GD-59* Szirmai, A., M. Prins and W. Schulte, *Tanzanian Manufacturing Performance in Comparative Perspective* (November 2002)
- GD-60* van Ark, Bart, Robert Inklaar and Robert McGuckin, *“Changing Gear” Productivity, ICT and Services: Europe and the United States* (December 2002)
- GD-61* Los, Bart and Timmer, Marcel, *The ‘Appropriate Technology’ Explanation of Productivity Growth Differentials: An Empirical Approach* (April 2003)
- GD-62* Hill, Robert J., *Constructing Price Indexes Across Space and Time: The Case of the European Union* (May 2003)
- GD-63* Stuivenwold, E. and M.P. Timmer, *Manufacturing Performance in Indonesia, South Korea and Taiwan before and after the Crisis; An International Perspective, 1980-2000* (July 2003)
- GD-64* Inklaar, Robert, Harry Wu and Bart van Ark, *“Losing Ground”, Japanese Labour Productivity and Unit Labour Cost in Manufacturing in Comparison to the U.S.* (July 2003)

Groningen Growth and Development Centre Research Monographs:

Monographs marked * are also available in pdf-format on the internet

- No. 1* van Ark, Bart, *International Comparisons of Output and Productivity: Manufacturing Productivity Performance of Ten Countries from 1950 to 1990* (1993)
(<http://www.eco.rug.nl/GGDC/pub/Arkbook.shtml>)
- No. 2 Pilat, Dirk, *The Economics of Catch-Up: The Experience of Japan and Korea* (1993)
- No. 3 Hofman, André, *Latin American Economic Development. A Causal Analysis in Historical Perspective* (1998)

- No. 4 Mulder, Nanno, The Economic Performance of the Service Sector in Brazil, Mexico and the United States (1999)
- No. 5* Smits, Jan-Pieter, Edwin Horlings and Jan Luiten van Zanden, Dutch
GNP and Its Components, 1800-1913 (2000)
(<http://www.eco.rug.nl/GGDC/PUB/dutchgnp.pdf>)
- No. 6 Sleifer, Jaap, Falling Behind, the East German Economy in Comparison with West Germany from 1936 to 2002 (2003)

